Invariant Moments Approach for Gujarati Numerals

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Abstract— **Due to less reported work for Gujarati numerals we have been motivated for same as Gujarati is a language not only of Indian states but widely spoken across world. We have. We have used noisy numerals for training and testing. Images are pre-processed and then subjected to the proposed algorithm. in our proposed algorithm we have used invariant moments as feature extraction technique and Gaussian distribution function as classifier. We found satisfactory results for some numerals. The results can be improved by giving better quality images for training and testing.**

***Index Terms*—Gujarati, Invariant moments,Gaussian distribution function .**

I. Introduction

From the reported work since decade together it has been reviewed that a meager amount of work has been done for computer based recognition of Gujarati numerals. Also apart from states of India, Gujarati is spoken by about 50 million across world in countries like Zimbabwe, Bangladesh, Tanzania, Fiji, Kenya, Oman, Malawi, Mauritius, Pakistan, Reunion, Singapore, Uganda, United Kingdom, USA, Zambia and South Africa. Gujarati is the derivation of the ancient Brahmi script, which is phonetic in nature. The Gujarati script was adapted from the Devanagari script to write the Gujarati language [1].

II. Literature Review

A. Gujarati Script

In the initial reported work, Antani & Agnihotri [2] in 1999 have given the primitive effort to Gujarati printed text. For feature extraction the author computed both invariant moments and raw moments. Also image pixel values are used as features creating 30x20= 600 dimensional binary feature space and performed classification using K-NN and minimum hamming distance classifiers. The best recognition rate was for 1-NN for 600 dimensional binary features space i.e. 67% 1-NN in regular moment space gave 48% while minimum distance classifier had the recognition rate of 39%. The Euclidean minimum distance classifier recognized only 41.33%. In the reported work, Patel & Desai [3] had contributed the efforts for skew detection and correction using radon transform. The radon transform based techniques of skew detection and correction procured results on the skew angle in the range of -20 to +20 degrees. Another effort contributed for Gujarati script was by Shah and Sharma [4] in which they used template matching and Fringe distance classifier as distance measure. They segmented printed characters in terms of lines, words and connected components. By this effort, for connected component recognition rate was 78.34% for upper modifier recognition rate was 50% where as for lower modifier it was 77.55% and for punctuation marks it was 29.6%, cumulative for overall it was 72.3%.

In another work, Yajnik [5] had proposed an approach of wavelet descriptors (Daubechies D4 wavelet coefficients) for image compression of printed Gujarati letters. They further computed coefficients which were considered as an input to the recognizer (like nearest neighborhood or Neural Network architectures [6]-[7]) that reported them with results up to 75% in compression. While reviewing literature, it was found that in 2005, Dholakia [8] have presented an algorithm to identify various zones. They have projected the use of horizontal and vertical profiles. These zones were identified by slope of lines created by upper left corner of rectangle created by the boundaries of connected components from line level and not word level the 3 different document images, 20 lines were extracted where 19 were detected with correct zone boundary. The line where it failed was very much skewed. Also the author [9] have used wavelet features, GRNN classifier and KNN classifier on the printed Gujarati text of font sizes 11 to 15 with styles regular, bold and italic by finding the confusing sets of the characters. He used two classifiers GRNN and KNN with Euclidean distance as similarity measure which resulted in 97.59 and 96.71 as their respective recognition rates.

In another work, Kayasth & Patel [10] proposed a system for recognition of offline computer generated and printed Gujarati characters using continuous GCRHMM for different font sizes of Gujarati characters. A continuous GCRHMM is used for the recognition, yielding classification accuracy Chaudhari [11] have described a system for recognition of offline multi-font computer generated and machine printed numerals. They have applied pre-processing techniques to the numerals. Followed by that they have used correlation based template matching where a numeral is identified by analyzing its shape and comparing its features that distinguish each numeral. In the work [12]-[13], the author proposed Template matching algorithm comprised of Template Classification, Correlation Analysis and Computation of Cross Correlation Coefficient. For each position a correlation coefficient was computed and the corresponding coordinates (pixel accuracy only) were saved and achieved 71.66 % as average overall recognition rate.

In the reported work of E.Hassan [14], the author used MKL for learning optimal combination of different features for classification. They performed multiclass classification Decision DAG framework. They reported the comparison of results in 1-Vs-1 framework and using KNN classifier .In the reported work Desai [15] have done preprocessing, skew

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correction upto 2degrees on the scanned images of Gujarati numerals. He then extracted four profile vectors which were used as an abstracted feature of identification of digit. Classification was done using feed forward back propagation neural network. The author recorded the success rate for standard fonts as 71.82%. In the another reported work of the author, subdivision of the skeletonized image and the aspect ratio of the image before converting it into skeleton were taken care of. He used k-NN classifier for classification of procuring the accuracy of 96.99% for training set and 92.783% for unseen data [16].

III. Feature Extraction Technique

Features of the images describe each numeral separately and distinctly For applying feature extraction and recognition techniques on the images of Gujarati numerals, we first needed to extract the features and then apply the recognition techniques to it. To carry out the task we employed an algorithm that can be used for feature extraction and recognition for Gujarati numerals

1. Take the input image from database
2. Resize it to 40x40
3. Complement the image
4. Binarize the image
5. Dilate the binarized image
6. Thinning of image is done so that extra pixels are removed
7. Apply Image Slicing Approach (Matrix 4x4, 5x5 and 8x8)Prior to find the features of the image, we needed to create a set for four separate feature sets namely;

   FS1: Image is not sliced
   FS2: Image is sliced in 4x4 zones
   FS3: Image is sliced in 5x5 zones
   FS4: Image is sliced in 8x8 zones

8. Apply Invariant Moments Approach
9. Use Gaussian distribution function as classifier
10. Compute the recognition rate on the basis of misclassified and properly classified numerals

Motivation for research on Gujarati numerals was considering the independencies of images on their position, size, orientation, and slant. For step 8 in above algorithm finding efficient invariant features was the key to solving this problem. Taking into consideration the independencies of basic transformation, we use Hu's [17] moment invariants technique for feature extraction. A set of seven invariant moments can be derived from (1) out of which six moments are absolute orthogonal invariants (and one skew orthogonal invariants) [18]-[20]

Equations of Invariant moments……. (1)

$$\phi_1 = \eta_{20} - \eta_{02}$$
$$\phi_2 = (\eta_{20} - \eta_{02})^2 - 4 \cdot \eta_{11}^2$$
$$\phi_3 = (\eta_{30} - 3 \cdot \eta_{12})^2 + (3 \cdot \eta_{21} - \eta_{03})^2$$
$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$
$$\phi_5 = (\eta_{30} - 3 \cdot \eta_{12}) \cdot (\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3 \cdot (\eta_{21} + \eta_{03})^2] + (3 \cdot \eta_{21} - \eta_{03}) \cdot (\eta_{21} + \eta_{03})[3 \cdot (\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$
$$\phi_6 = (\eta_{20} - \eta_{02}) \cdot (\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4 \cdot \eta_{11} \cdot (\eta_{30} + \eta_{12}) \cdot (\eta_{21} + \eta_{03})$$
$$\phi_7 = (3 \cdot \eta_{21} - \eta_{03}) \cdot (\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3 \cdot (\eta_{21} + \eta_{03})^2] + (3 \cdot \eta_{12} - \eta_{30}) \cdot (\eta_{21} + \eta_{03})[3 \cdot (\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

We computed these features on the character image and its changed versions that were prepared by applying various parameters in preprocessing. These computed features were then stored in a file. This database was working as template for the test images that were compared runtime. The test images were also subjected to the same above algorithm. The classification was decided on the basis of steps 9 and 10 of above algorithm.

IV. Experimental Results

On the basis of FS1, FS2, FS3and FS4 computed and stored earlier, the 80 test images of each numeral were treated up with above algorithm and then using Gaussian distribution function as classifier the following results were reported.

Table 1 Confusion matrix for invariant moments using Gaussian distribution function for FS1

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	**67**	0	0	0	1	8	2	1	0	1
1	0	**53**	0	1	11	0	9	5	0	1
2	2	2	**16**	0	29	4	17	8	0	2
3	1	1	6	**20**	1	6	25	6	1	13
4	3	6	1	1	**59**	2	6	1	1	0
5	5	8	3	0	10	**30**	18	3	0	3
6	2	10	1	5	3	10	**43**	5	0	1
7	3	13	0	0	9	4	8	**40**	0	3
8	2	0	1	0	2	1	1	0	**59**	14
9	5	1	2	0	4	13	1	5	4	**45**

Table 2 Confusion Matrix for invariant moments using Gaussian distribution function as classifier for FS2

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	**66**	0	0	0	1	10	1	0	0	2
1	0	**57**	0	0	12	1	4	6	0	0
2	2	2	**15**	1	33	8	10	7	0	2
3	1	1	5	**26**	1	7	22	6	1	10
4	4	4	0	0	**60**	6	3	2	1	0
5	5	7	1	0	4	**38**	11	9	0	5
6	2	8	1	3	5	23	**31**	5	0	2
7	3	11	1	0	8	5	4	**43**	0	5
8	0	0	1	0	2	2	0	1	**63**	11
9	2	0	1	1	6	14	0	4	3	**49**

Table 3 Confusion matrix for invariant moments using Gaussian distribution function for FS3

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	**74**	0	0	0	0	3	1	2	0	0
1	0	**42**	0	1	13	4	9	4	0	7
2	7	9	**13**	0	29	12	7	0	0	3
3	0	14	6	**16**	5	7	19	3	1	9
4	5	8	0	0	**53**	8	5	0	1	0
5	3	6	0	0	12	**44**	8	2	0	5
6	2	26	1	1	4	19	**22**	3	0	2
7	11	18	0	0	2	4	5	**33**	0	7
8	4	1	0	0	2	0	0	0	**69**	4
9	3	8	5	2	5	2	1	6	2	**46**

Table 4 Confusion matrix for invariant moments using Gaussian distribution function for FS4

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	**73**	0	0	0	1	3	0	3	0	0
1	0	**51**	0	1	10	2	6	9	0	1
2	4	7	**18**	1	23	7	9	9	0	2
3	2	3	5	**13**	1	15	17	9	1	14
4	6	3	2	0	**52**	7	4	5	1	0
5	4	11	2	0	10	**26**	17	8	0	2
6	2	10	2	1	6	10	**35**	11	0	3
7	5	11	0	0	8	4	4	**48**	0	0
8	1	1	0	0	2	2	0	1	**64**	9
9	4	0	3	2	2	21	1	8	2	**37**

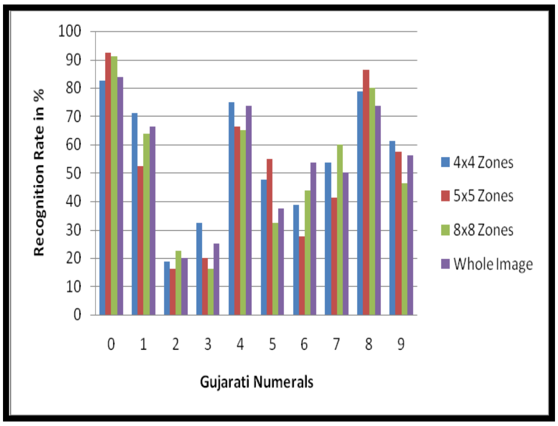

Fig 2 Comparison of the image slicing approach and whole image for invariant moments using Gaussian distribution function

For our experiments, we have considered noisy numerals and also no skew correction techniques are implemented. As seen from figure 2 for numeral 0 we reported the recognition rate as 92.5%, for numeral 1 as 71.25%. For numerals 2, 3 and 6 less recognition rates were recorded as 22.5%, 32.5% and 53.75% respectively. Numerals 4, 5, 7 and 9 showed some better results as compared to 2, 3 and 6 as 75%, 55%, 60% and 61.25% respectively. Numeral 8 reported to have recognition rate 86.25%. It has been noted that among all these recognition rates numeral 0 scored a maximum of 92.5%. The overall recognition rate was 61.25% which was very low but it showed good results for numerals 0 and 8.

Table 5 Confusion matrix for invariant moments using Gaussian distribution function for optimum mean and standard deviation

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0	**75**	0	0	0	0	3	0	2	0	0
1	0	**58**	0	0	12	1	4	5	0	0
2	6	0	**41**	1	3	0	0	9	1	19
3	1	1	3	**39**	3	5	12	3	1	12
4	1	0	0	1	**72**	2	1	0	1	2
5	2	7	0	0	10	**53**	3	0	0	5
6	2	10	1	5	3	10	**43**	5	0	1
7	2	1	0	0	6	7	7	**53**	0	4
8	0	1	0	0	3	1	0	0	**74**	1
9	1	0	0	0	3	2	0	12	1	**61**

Though the input image was noisy numeral 0 is being correctly recognized for 93.75% as shown in figure 5.8 while it has been misrecognised as 5 and 7 for 3.75% and 2.5% respectively. Misclassification for numeral 2 is numeral 6 and 3 rest no other numeral is misclassified as 2. Numeral 1 is misclassified as 4 for 15%. Numeral 8 is confused with 1, 4, 5 and 9. Numeral 8 reported to have recognition rate of 92.5%. Numeral 9 is a two-part symbol so it is highly misclassified as 7. Overall recognition rate is approximately 72 %. Though it is proving less promising for overall results but it has show good results for numeral 0, 4 and 8 as compared with results put forward by Desai [15]-[16]. The recognition rate is low because data set has poor quality of numerals with no constraints for pen, ink or numeral size. It may improve if the good quality numeral images are given for recognition

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